

Multi-Stage Optimization of Electronic Product Control and Cost Based on Sampling and Testing

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Abstract. In the production control of electronic products, more and more people are concerned about the optimization of cost-effectiveness. This paper investigates the quality control and cost optimization problems in the production process of electronic product manufacturing enterprises, and proposes a decision optimization model especially for the complex multi-stage production process. Spare parts quality sampling and testing, finished product testing and the treatment of unqualified finished products. This paper proposes a stratified sampling and inspection module and a two-step sampling and inspection model to optimize the inspection process, reduce the cost, and improve the inspection accuracy and reliability. And it is able to analyze the total cost and the number of cycles in conjunction with optimizing the decision-making after each stage of production to arrive at the cost-optimal solution. For multi-process and multi-part production scenarios, the optimization model has achieved significant results in defective rate control and production efficiency improvement. Through model solving and data analysis, optimization strategies are proposed to achieve the quality control objectives and cost minimization of the enterprise.

Keywords: Sampling and testing, Cost optimization, Defective rate control, Production decision models.

1. Introduction

The electronics manufacturing industry is a highly complex and competitive industry. Traditional production management methods are often difficult to cope with the current highly automated and complex production processes, so how to optimize the production process through scientific models and data-driven methods has become a common focus of attention in both academia and industry.

In past studies, many academics and researchers have mainly adopted statistical quality control models (e.g., Shewhart control charts [1], CUSUM control charts [2][3], etc.) to realize the monitoring and management of quality in the production process. These models are usually based on historical data and provide real-time monitoring and feedback on quality deviations that may occur during the production process, ensuring that corrective actions can be taken quickly when products deviate from the set standards. In addition, models such as the Economic Output Quantity (EOQ) model and the Closed Loop Supply Chain model, which focus on the balance between production costs, inventory holding costs and order processing costs, are also used to optimize a company's production and inventory management decisions.

The work in this paper combines statistical quality control and a multi-stage dynamic optimization model, which integrates the balance between quality and cost through hierarchical sampling inspection and dynamic optimization strategies in different production stages. First, a two-step inspection model is introduced to improve the inspection efficiency and reduce the error of defective. This paper, several key optimization metrics are used in the model building and solving process, including defective rate control, inspection cost, assembly cost, disassembly cost and return processing cost. Through these metrics, we are able to quantify the impact of different production decisions on the overall cost and evaluate the advantages and disadvantages of different strategies. The experimental results show that the multi-stage production optimization model proposed in this paper has significant advantages in inspection efficiency, defective rate control and cost savings. The model exhibits high decision accuracy at both 90% and 95% confidence levels, and through multiple

rounds of cyclic optimization, it finally achieves a significant reduction in the defective rate and a significant saving in the total cost. The main contribution points are as follows:

This paper proposes a hierarchical sampling and inspection module and a two-step sampling and inspection model that optimizes the inspection process, reduces costs and improves inspection accuracy and reliability.

This paper proposes a multi-stage dynamic optimization module, establishes a dynamic optimization model, optimizes the decision-making in each stage of production, analyzes the total cost and the number of cycles, and arrives at a cost-optimal solution.

In this paper, a complex process cost control optimization module is proposed to establish a comprehensive cost model for the multi-process, multi-part production process, which achieves a balance between defective rate control and cost-effectiveness.

2. Related work

2.1. Parts quality control and sampling

In recent years, spare parts quality control and sampling and inspection technologies have been developing continuously, especially under the impetus of intelligent manufacturing and big data technologies, automated inspection and intelligent sampling methods are widely used. Manual inspection is gradually replaced by automated inspection equipment and algorithms. Chang et al [4] proposed a multi-objective optimization model, which is specifically used to deal with multiple errors in inspection, by comprehensively considering the inspection cost, product quality, and inspection errors, but the effect decreases as the types of errors increase. Jing et al [5] proposed a multi-objective optimization model specifically for dealing with multiple errors in inspection, but it performs poorly for large variance. Sundaram et al [6] combined smart manufacturing with traditional quality control methods can significantly improve the inspection efficiency, but it is not sensitive to some traditional industrial problems.

2.2. Multi-stage decision-making dynamic optimization

Multi-stage production decision-making and dynamic optimization is a challenging research topic in modern manufacturing systems because it involves multiple interdependent decision-making processes and resource allocation problems in dynamic environments. In recent years, researchers have proposed a variety of models and methods to cope with the dynamic optimization problems in complex production systems. Zhang et al [7] explored a cross-docking-based unitization process for factory logistics, which is applicable to problems involving logistics and dynamic production decision-making in complex production environments. However, it is not sensitive enough for single logistics processing. Torball et al [8] proposed a real-time truck scheduling model based on a multi-agent system, which is applicable to the cross-docking problem of a single inbound and outbound door. However, the problem of simultaneous docking of multiple objects is not handled well enough. Li et al [9] proposed an integrated optimization method based on mixed-flow shop floor scheduling, through which this optimization tool effectively reduces delays in the production process.

2.3. Multi-process production optimization

Optimization of complex production with multiple processes and parts is an important research topic in modern manufacturing industry, especially in the environment of multi-species and small-lot production. In recent years, with the development of Industry 4.0 technology, researchers have proposed many innovative methods in the field of optimization of complex production systems. Wu et al [10] proposed a multi-objective meta-heuristic algorithm to deal with complex optimization problems including non-displacement assembly line scheduling. Although it can optimize the production performance to a certain extent, it is not ideal for cost control. Kovačević et al [11] proposed a production planning model under stochastic capacity constraints, which optimizes production planning and inventory management by considering different constraints in the production

and remanufacturing processes. However, there is no significant improvement in the efficiency of production. Polenghi et al[12] used blockchain technology and case-based reasoning approach to optimize the production process, which improves the efficiency of decision making in complex production environments.

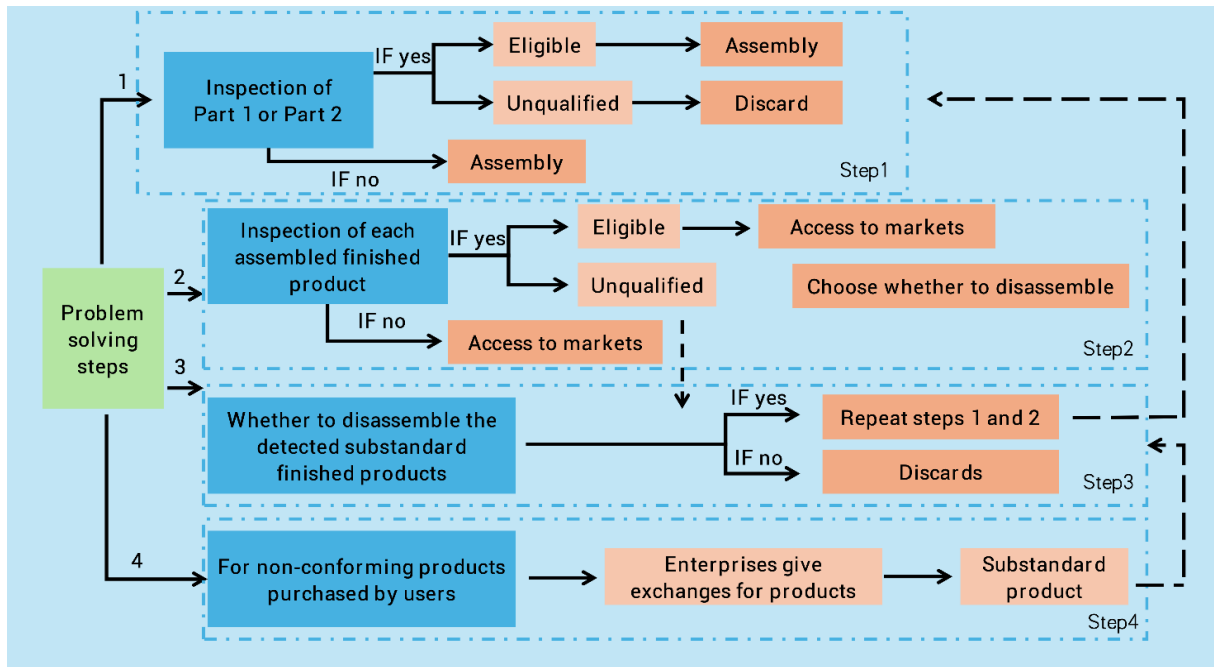


Figure 1. Production quality control and cost-effective optimization of the complete flow chart

3. Model

In this paper, as shown in Figure 1, this model is constructed based on sampling inspection and dynamic optimization for the multi-stage decision-making problem in the production process. The model mainly focuses on the key links in the quality inspection of spare parts, quality control of finished products and treatment of unqualified finished products in electronic product manufacturing enterprises and achieves the optimization of the production process and minimization of costs by setting reasonable inspection schemes and cost control strategies.

3.1. Two-step sampling and testing model

In the early stage of production, the inspection of spare parts quality determines the quality of the finished product, so sampling inspection of spare parts is essential. In this paper, a two-step sampling inspection model is proposed to control the inspection cost through a hierarchical sampling strategy. As shown in Figure 2, the two-step test model contains a multi-step design.

The core of the model is to effectively control the rate of defective products and inspection costs through hierarchical sampling. In the first stage, a smaller sample size is selected for initial screening, and if the initial detection cannot clearly determine the quality of the product, then it enters the second stage to expand the sample size to improve the accuracy of detection. The sample size of the first stage is set as $Q_1=60$, the number of detected defective products is F_1 , and the sample defective rate is: $P_1 = \frac{F_1}{Q_1}$. The testing rules are as follows: if $p_1 < 4\%$, the batch of spare parts is accepted directly; if $p_1 > 16\%$, the batch of spare parts is rejected; if p_1 is between 4% and 16% , the batch goes to the second stage of testing. The sample size of the second stage is increased to $Q_2=148$ and the defective rate is $P_{total} = \frac{F_1 + F_2}{Q_1 + Q_2}$.

The model evaluates whether the quality of spare parts provided by the supplier meets the nominal standards through hypothesis testing. The null hypothesis H_0 : the defective rate of spare parts $a \leq 10\%$

and the alternative hypothesis H_1 : the defective rate $a > 10\%$ are set. Calculate the decision criteria by statistical methods at the given confidence level. For binomial distribution problems, use the normal distribution approximation when the sample size is large:

$$Z = \frac{P_{brochure} - P_{standardized}}{\sqrt{P_{standardized}(1 - P_{standardized})/n}} \quad (1)$$

Where $P_{brochure}$ is the sample defective rate, $P_{standardized}$ is the nominal defective rate, n is the sample size. Based on the Z -value, the batch is accepted or rejected. In the first stage, set the acceptance criterion at 90% confidence level and the rejection criterion at 95% confidence level. When $p_1=0.04$, calculate the Z -value, if the Z -value corresponds to a confidence level higher than 90%, then accept; when $p_1=0.16$, calculate the Z -value, if the Z -value corresponds to a confidence level lower than 5%, then reject.

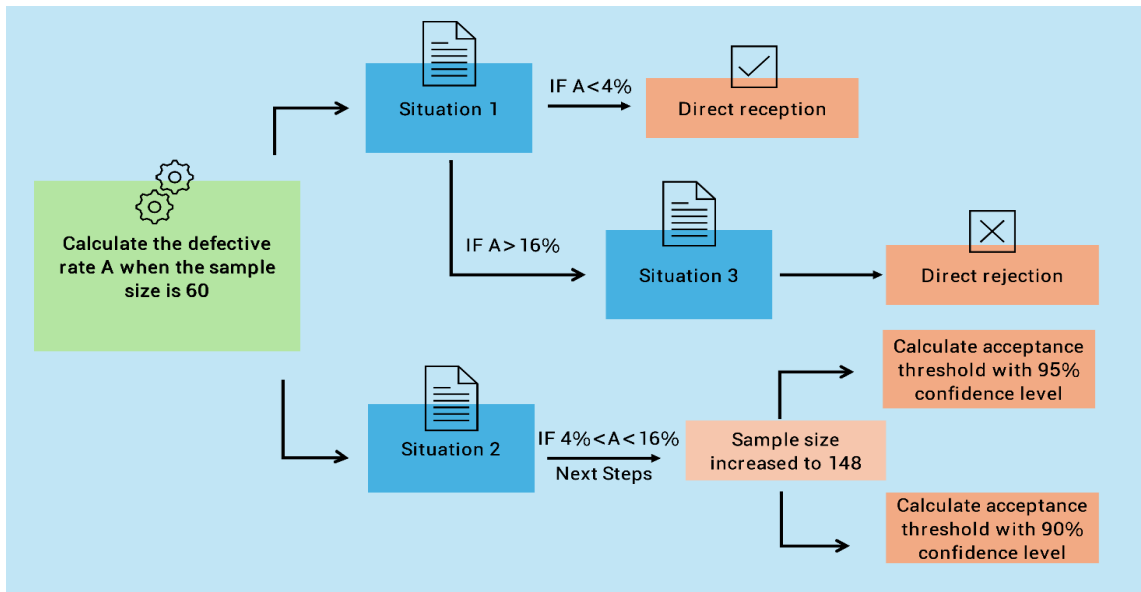


Figure 2. Flowchart of the two-step test model

3.2. Multi-stage dynamic optimization model

The dynamic optimization model proposed in this paper minimizes the total cost by adjusting the production decisions at each stage. In the dynamic optimization model, several decision variables are defined: m_1, m_2 denote whether or not to detect spare part 1 and spare part 2, respectively, and take the value of 0 or 1. n Whether or not to detect the finished product; g Whether or not to dismantle the unqualified finished product; and h Whether or not to dispose of unqualified products returned by users. With these decision variables, the model constructs a cost function for each stage. The total cost includes the following components: Parts Inspection Costs, Finished Product Inspection & Assembly Costs, Disassembly & Reconstruction Costs, Returns Processing Costs.

$$C_{\text{spare part}} = \sum_{i=1}^2 (m_i \cdot C_{\text{sensing}} + (1 - m_i) \cdot a_i \cdot C_{\text{substandard products}}) \quad (2)$$

$$C_{\text{Finished product}} = n \cdot C_{\text{Inspection}} + (1 - n) \cdot a_{\text{Fin-product}} \cdot C_{\text{Sub-products}} \quad (3)$$

$$C_{\text{Dismantling}} = g \cdot C_{\text{Dismantling}} + a_1 \cdot C_{\text{Parts 1}} + a_2 \cdot C_{\text{Parts 2}} \quad (4)$$

$$C_{\text{Returns}} = h \cdot C_{\text{Processing Returns}} + a_1 \cdot C_{\text{Parts 1}} + a_2 \cdot C_{\text{Parts 2}} \quad (5)$$

After each round of testing, the defective rate decreases, assuming that the defective rate decreases by a fixed percentage, Eq: $a_{i+1} = a_i \cdot (1 - \beta)$. Where β is the decreasing proportion of the defective rate. By recursively calculating the defective rate after each round of detection, the model is able to

dynamically adjust the detection and production strategy as a decreasing proportion of the defective rate.

3.3. Optimization of multi-process and multi-component production

For the complex production process with multiple processes and parts, the model optimizes the inspection strategy for each link. For each part and finished product, the model achieves global optimization of the production process by defining different decision variables for inspection and disassembly. In a multi-process scenario, the defective rate is passed between processes. Setting x spare parts are transformed into semi-finished products through two processes, the defective rate transfer formula is: $a_{\text{semi-manufactured goods}} = a_{\text{Spare parts 1}} \cdot a_{\text{Spare parts 2}}$. During the inspection of semi-finished products, the rate of defective products gradually decreases and finally reaches a minimum level at the finished product stage. The model calculates the cost of each round by means of a recursive algorithm and stops the inspection when the defective rate drops to a predetermined threshold, or the number of inspection cycles reaches an upper limit. The recursive formula is:

$$C_{\text{total}} = \sum_{i=1}^T (C_{\text{spare part}} + C_{\text{Finished products}} + C_{\text{Dismantling}} + C_{\text{Returns}}) \quad (6)$$

Through simulation experiments and data analysis, the model finds the balance point between decreasing defective rate and cost, and optimizes the cost structure of the whole production process. This model achieves quality control and cost minimization of spare parts and finished products through two-step sampling inspection and dynamic optimization decision. In the complex multi-process, multi-part scenario, the model effectively optimizes the production process and improves the productivity and economic efficiency of the enterprise.

4. Results

In order to verify the effectiveness of the multi-stage production optimization model based on sampling inspection proposed in this paper, we conducted simulation experiments through Python code. The main objective of the experiment is to evaluate the impact of different decision-making strategies on the control of production cost and defective rate, and to find the optimal combination of strategies in the production process.

4.1. Experimental design

The test objects in the experiment are two key parts and the final assembled product. Different initial values are set for the defective rate of each part, and the experiment calculates the inspection cost, the dynamic change of the defective rate, and the pass rate of the final product through multiple rounds. To ensure the accuracy of the experimental results, we conducted experiments at different confidence levels (90% and 95%) to evaluate the decision-making efficiency and cost performance at different confidence levels. Spare parts sampling and testing: The experiment begins with sampling and testing of spare parts 1 and 2, and decides whether to accept the batch or not, or whether it is necessary to expand the sampling for a second test based on the test results. Finished product testing: the assembled finished product to calculate the defective rate and decide whether to test the finished product. The formula for calculating the defective rate of finished products is:

$$P_{\text{finished product}} = P_{\text{Spare part 1}} \cdot P_{\text{Spare part 2}} \quad (7)$$

Cyclic inspection with decreasing defective rate: After each round of inspection, the defective rate is updated according to a set decreasing percentage. Assuming that the defective rate decreases by 10% in each round, the new defective rate will be: $P_{\text{new}} = P_{\text{old}} \cdot (1 - 0.1)$. Costing: After each cycle, the total cost of each stage is calculated, including the cost of parts inspection, finished product inspection, assembly cost, and disassembly cost. The total cost formula:

$$C_{\text{total}} = C_{\text{Spare part}} + C_{\text{Finished Product Inspection}} + C_{\text{Assembly}} + C_{\text{Dismantling}} \quad (8)$$

Table.1. Decision analysis results at 90% confidence level

	Inspection of spare parts 1	Inspection of spare parts 2	Inspection of finished products	Dismantling	Total Cost	Number of cycles
0	False	False	True	True	16.99	1
1	False	False	False	True	33.45	2
2	False	False	True	True	16.36	1
3	False	False	True	True	29.04	2
4	False	False	False	True	28.50	2
5	False	False	False	False	2.63	1

Table.2. Decision analysis results at 95% confidence level

	Inspection of spare parts 1	Inspection of spare parts 2	Inspection of finished products	Dismantling	Total Cost	Number of cycles
0	False	False	True	True	17.12	1
1	False	False	False	True	33.42	2
2	False	False	True	True	16.18	1
3	False	False	True	True	29.35	2
4	False	False	False	True	28.64	2
5	False	False	True	False	4.14	1

4.2. Analysis of experimental results

According to the results of the experiment, the initial defective rate of Part 1 is low, and the experiment shows that the defective rate of this part can be rapidly reduced to less than 5% after several rounds of testing, so it is recommended that no sampling and testing be carried out for Part 1. In contrast, Part 2 has a high initial reject rate, which can lead to a high reject rate of the finished product if no treatment measures are taken after testing. Therefore, it is recommended that Part 2 be tested at least twice to ensure that parts entering assembly are acceptable. As shown in Table1 and Table2, the results are different at different confidence levels. The finished product defective rate will change according to the quality of spare parts, and the experiment found that when the defective rate of spare part 2 is higher, the finished product defective rate is also higher accordingly, so it is necessary to carry out strict testing of the finished product in order to prevent substandard products from flowing into the market.

Once the defective rate of part 1 is reduced to less than 5%, stopping the testing of this part can save at least 300 in testing costs. The experimental results show that the defective rate shows a decreasing trend after multiple rounds of testing, especially after the second round of testing, the defective rate is significantly reduced. In terms of the number of cycles, 2-3 cycles can control the defective rate below 5% in most cases, which is in line with the set threshold. Therefore, in production practice, costs can be further optimized by reducing the number of cycles, but it is necessary to ensure that the defective rate meets the requirements.

In order to show the experimental results more intuitively, we visualize the defective rate and total cost at different confidence levels. Table 1 shows the variation of defective rate of part 1, part 2 and finished product at 90% and 95% confidence levels, while Table 2 shows the variation of total cost with the number of inspection cycles. At the 95% confidence level, the defect rate drops rapidly after the second inspection, from 15% to less than 5% for Part 2. In contrast, at the 90% confidence level, the defective rate decreases more slowly, and the 95% confidence level has a significant advantage in controlling the defective rate of Part 2 in particular. The total cost changes the total cost increases with the number of inspections cycles, but stabilizes after the second inspection. 95% confidence level, although the number of inspections is higher, the final total cost is lower than 90% confidence

level, which shows that increasing the number of inspections is effective in reducing the extra cost caused by defective products.

5. Conclusions

This paper systematically solves the quality monitoring and decision-making problems at all stages of production by constructing a two-step sampling inspection model, a dynamic optimization model, and a multi-process, multi-spare-parts production optimization model. The experimental results show that the model proposed in this paper can effectively balance the contradiction between production cost and quality control. The experimental results at different confidence levels show that although increasing the inspection stringency increases the inspection cost, it can significantly reduce the defective product rate, thus reducing the return, disassembly and reorganization costs due to unqualified products. In addition, the research in this paper emphasizes the importance of dynamic decision making in complex multi-process production scenarios. Through the flexible adjustment of different production stages, enterprises can dynamically optimize the inspection strategy of each stage based on historical data and real-time production information to achieve a balance between cost and quality. In conclusion, the research in this paper provides practical solutions for electronic product manufacturers in quality control and cost optimization. Future research can further extend the model to explore more complex production scenarios as well as introduce machine learning algorithms to enhance the intelligence and flexibility of the decision-making process.

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